A Health Monitoring Framework for Thermal Degradation Mitigation in Solar Power Plants

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Abstract

Prognostics and Health Management (PHM) of photovoltaic (PV) systems requires integrated approaches that link temperature forecasting with physical degradation modeling under thermal stress. This study addresses key limitations of existing PHM frameworks, such as the lack of high-resolution climate projections and limited coupling with degradation models, by proposing a unified PHM methodology tailored for high-temperature scenarios. The framework consists of three main components: (1) a formal problem definition of PV performance loss during extreme temperature and high cooling demand periods; (2) high-resolution spatiotemporal forecasting of temperatures; (3) probabilistic modeling of PV thermal degradation. The proposed approach integrates two innovations, including a Gaussian copula–based risk assessment for capturing joint distributions of environmental stressors (e.g., air temperature, solar irradiance, and wind speed) and a Spatiotemporal Graph Neural Network (ST-GNN) architecture for accurate prediction of extreme temperature events. Accelerated aging tests and ERA5 reanalysis data (1974–2023) have been used to parameterize the probabilistic aging models. Preliminary results from forecasting experiments achieved root-mean-square errors of 5.1–5.5°C across three representative Spanish climate zones. Future work will focus on enhancing the expressiveness of spatial dependencies through dynamic graph structures with learnable edge weights, as well as propagating predictive uncertainty from temperature forecasts into degradation models using uncertainty quantification techniques.

1. Introduction and Background

The accelerating effects of climate change have introduced significant global challenges, particularly evident through extreme weather events that disrupt ecosystems, infrastructure, and society. Among these challenges, the energy sector faces unprecedented risks, as extreme weather events impact both energy demand and the reliability of energy infrastructure (Perera, Nik, Chen, Scartezzini, & Hong, 2020). The Earth's climate system is a dynamic interplay of atmospheric and oceanic forces (Wang et al., 2024). While there have always been challenges in the prediction of climate patterns, human-induced climate change has hindered the predictions even more with the increased frequency and intensity of extreme meteorological events (Gonçalves, Costoya, Nieto, & Liberato, 2024).

The rapid global deployment of PV systems is critical for achieving decarbonization and reducing the cost of energy production, yet climate change–driven heatwaves threaten both their performance and longevity (Chang & Han, 2024).

In the context of PHM, systematic frameworks have been developed to monitor, diagnose, and predict asset degradation, but existing PHM solutions for PV plants rarely integrate temperature extremes forecasts with the physics of aging, limiting proactive maintenance strategies (Chang & Han, 2024). A unified solar energy management framework that combines extreme temperature forecasting with PV degradation modeling is needed to safeguard solar energy infrastructure under increasing thermal stress in the presence of extreme weather events.

2. PROBLEM STATEMENT

Extreme temperatures have accelerated ageing processes in PV modules, including solder joint fatigue, encapsulant browning, and cell metallization wear. These phenomena can lead to efficiency losses of up to 25% during periods of peak demand, which correspond to the times of day when cooling loads are at their highest (Aghaei et al., 2022). This, in turn, can compromise grid reliability.

Current methodologies for extreme temperature management in PV power plants are deficient in the sense that they lack a unifying probabilistic framework that (1) forecasts temperature intensity, duration, and spatial extent with quantified uncertainty and (2) directly integrates those forecasts into degradation models to predict PV module lifetime under extreme temperature conditions.

3. EXPECTED NOVEL CONTRIBUTIONS TO THE FIELD

- **Integrated PHM framework for thermal degradation in PV systems.** This research will establish a unified PHM framework that directly couples probabilistic temperature forecasts with PV module degradation models. The framework enables end-to-end prediction and management of thermal degradation in solar panels by ingesting and forecasting temperature profiles rather than raw meteorological inputs into aging models. Unlike conventional approaches that treat forecasting and health modeling as separate tasks, this solution ensures that uncertainty in extreme temperature predictions are taken into account in the degradation estimations.
- **High resolution, uncertainty aware forecasting.** Integration of Graph Neural Networks (GNNs) to capture spatial dependencies to increase the reliability of these forecasts for forecasting and PHM decision making in different geographic locations.
- **Unified prognostic framework.** Predictive risk assessment framework that integrates temperature prediction models with PV panel degradation models, allowing quantification of the impacts of extreme heat events on PV panels.

4. RESEARCH PLAN

4.1. Specific Objectives

- To develop a probabilistic risk assessment framework to quantify multivariate environmental stressors and their joint impact on renewable power plant components under extreme temperature conditions.
- To design and implement a spatiotemporal forecasting system using GNNs and ERA5 reanalysis data, that predicts extreme temperature events up to 96 hours in advance, capturing both spatial dependencies and temporal dynamics.
- To incorporate forecast accuracy at different geographic locations to determine the optimal aggregation level for reliable temperature predictions in PHM applications.
- To integrate probabilistic temperature forecasts with PV panel degradation models to quantify the effect of extreme heat on module health and enable predictive maintenance decision-making.

4.2. Methodology

A three-phase methodology has been defined, For the development and validation of a PHM framework for predicting high-temperature degradation in photovoltaic systems.

Phase 1. Probabilistic degradation modeling

1. **Data acquisition and preprocessing.** Historical meteorological records and PV performance measurements are gathered and standardized.
2. **Statistical and sensitivity analysis.** Stressors and degradation responses are correlated, and sensitivity metrics are derived to inform model structure.
3. **Model construction.** Gaussian-copula models are developed to represent probabilistic degradation under thermal stress.
4. **Validation.** Model forecasts are compared against accelerated aging experiment results to assess accuracy.

Phase 2. Spatiotemporal temperature forecasting

1. **Feature engineering.** Temporal predictors (trend, seasonality) and spatial predictors (terrain, land cover) are extracted from reanalysis datasets.
2. **ST-GNN development.** A Spatiotemporal Graph Neural Network is designed to predict temperature extremes over different time horizons.
3. **Uncertainty quantification.** Evaluate multiple uncertainty estimation techniques, including conformal prediction, Bayesian neural networks, and deep ensembles, against held-out data to identify the most accurate and computationally efficient method. Integrate the selected approach into the ST-GNN pipeline to produce well-calibrated probabilistic intervals for each spatiotemporal forecast.
4. **Validation.** To ensure practical applicability and assess performance under different environmental conditions, the forecast skill and reliability are evaluated using multiple regional case studies. These case studies are strategically selected to represent a range of climatic zones, providing a comprehensive assessment of the framework's capabilities in diverse operational settings relevant to solar power plant deployments.

Phase 3. Integrated PHM framework

1. **Model coupling.** Forecast outputs (temperature) are linked to degradation models to estimate PV health prognostics.
2. **Uncertainty propagation.** Forecast uncertainty is propagated to yield predictions with confidence intervals.
3. **Case study validation.** The integrated framework is subjected to rigorous testing through multiple regional installations and is benchmarked against observed performance declines.

5. PRELIMINARY WORK AND RESULTS

5.1. Probabilistic degradation modeling

This research phase implements a probabilistic aging framework for crystalline silicon PV panels, including monocrystalline and polycrystalline types, in which environmental stressors, ambient temperature, irradiance, and humidity drive degradation rates. The model employs Gaussian-copula representations of joint extreme-event distributions to simulate realistic thermal-stress scenarios and computes an aging-acceleration factor that feeds into cumulative loss-of-life calculations. To date, the following tasks have been completed:

- Characterized PV degradation mechanisms under thermal stress, adopting the SANDIA temperature model to estimate module operating temperatures from ambient conditions, irradiance, and wind speed (King, Boyson, & Kratochvil, 2004).
- Implemented an empirical lifetime model in which an aging acceleration factor, dependent on maximum module temperature, daily temperature swings, irradiation, and humidity, are used to compute cumulative loss-of-life over time.
- Calibrated and benchmarked the Kaaya thermal-cycling degradation model (Kaaya, Koehl, Mehilli, de Cardona Mariano, & Weiss, 2019) and the Subramaniyan environmental-stress degradation model (Subramaniyan, Pan, Kuitche, & TamizhMani, 2018) against site-specific performance data, revealing conflicting severity assessments that underscore the need for a unified Gaussian-copula–based probabilistic risk framework.
- Fitted Gaussian copulas to the joint distribution of daily extreme ambient temperature, humidity, and irradiance for two large U.S. solar farms (Copper Mountain and Mount Signal II). Fig. 1 shows the joint cumulative probability distribution functions plotted in bivariate plots. This visualization highlights the extreme values (A and B) identified by the cumulative distribution function (CDF) thresholds, which are highlighted in red. The modeled copulas closely match observed cumulative probabilities and pass Anderson–Darling goodness-of-fit tests (Kitani, Ma, & Murakami, 2024).
- Conducted site-specific analyses revealing that wildfire-driven extremes, simultaneous peaks of 972 W/m² irradiance, 41 °C ambient temperature, and 69% relative humidity during the Aspen Fire on July 23, 2013, induced the most severe instantaneous module aging at Mount Signal II (7.52 h of life lost).
- Developed a PV risk index by combining multivariate extreme-event probabilities (via Gaussian copulas of temperature and irradiance) with instantaneous aging rates. The index identifies wildfire-related extremes as the primary drivers of accelerated PV degradation and supports data-driven prioritization of maintenance and resilience planning.

5.2. Spatiotemporal temperature forecasting

Time-Series Modeling. Hourly ERA5 reanalysis data (1974 – 2023) were processed into high-resolution grids of pressure-level and surface temperature variables (Hersbach et al., 2023). Key temporal features (trend, seasonality, autocorrelation) were extracted and used to train three forecasting models Autoregressive Integrated Moving Average (ARIMA), Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN)–LSTM via region-specific pipelines in Seville, Badajoz, and Alonsotegi (Spain). Bayesian optimization tuned hyperparameters. Performance metrics (Root-Mean-Square Error (RMSE), Mean Absolute Error (MAE)) showed that:

- CNN–LSTM attained the lowest RMSE in Seville (5.2 °C) and Badajoz (5.5 °C).
- LSTM was no optimize in Alonsotegi (RMSE = 5.1 °C), reflecting its complex oceanic climate.

Spatio-Temporal Graph Neural Network (ST-GNN). An Attention-enhanced Temporal Graph Convolutional Network was evaluated for 12 h, 24 h, and 36 h temperature forecasts over a fully connected ten-node graph (Iskandaryan, Ramos, & Trilles, 2023). The model is trained exclusively on the two-metre air temperature variable, without incorporation of additional meteorological features such as humidity or irradiance. The 12- and 36-hour ahead predictions achieved an MSE of 0.054 and 0.059, and a MAE of 0.187 and 0.189, respectively, but failed to capture the overall trends; in contrast, the 24-hour ahead horizon offered better results with an MSE of 0.06 and a MAE of 0.198, demonstrating the most accurate alignment with the observed temperature profiles shown in Fig.2.

5.3. Insights and next steps

The preliminary results confirm that the Gaussian copula–based probabilistic aging model and the ST-GNN temperature-forecasting approaches can be seamlessly integrated into a cohesive PHM framework. The limited impact

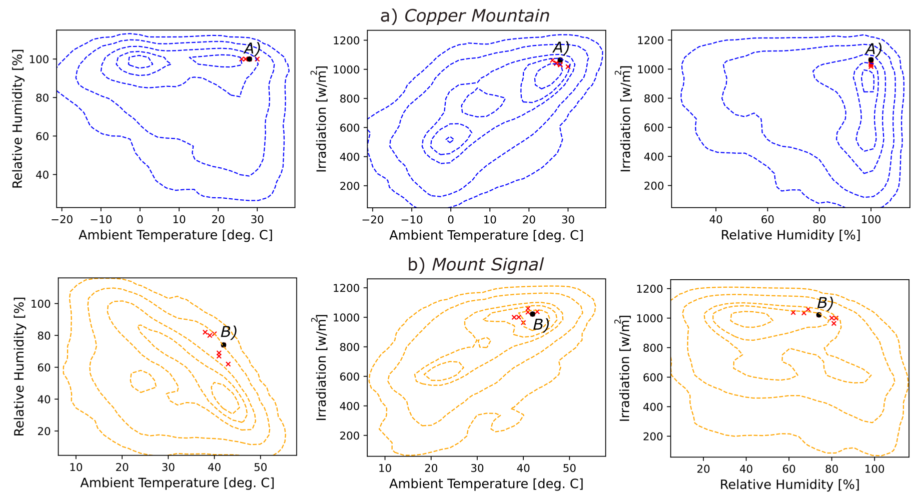

Figure 1. Joint probability distribution hourly for PVs in (a) Copper Mountain and (b) Mount Signal.

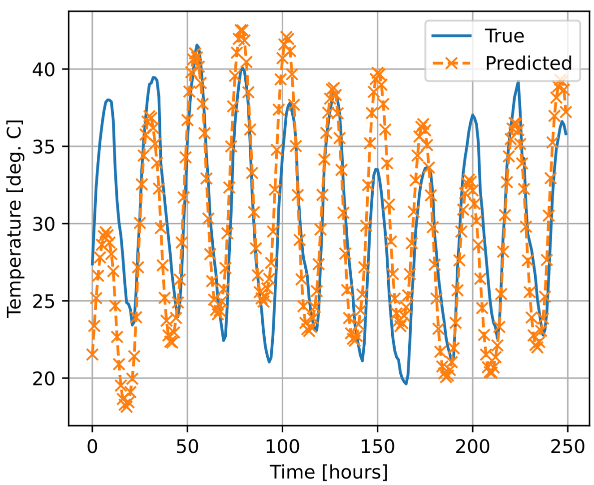

Figure 2. True vs. predicted temperature for a 24-hour ahead forecasting horizon using the ST-GNN model.

of basic spatial encodings underscores the need for richer spatial representations.

Next steps:

- Introduce dynamic graph architectures with learnable edge weights to more accurately model spatial interactions among weather stations.
- Compare and evaluate uncertainty-quantification techniques against held-out data to identify the most accurate and computationally efficient approach, then integrate the selected method into the aging model to generate well-calibrated degradation intervals.
- Validate the coupled forecasting–degradation framework on multiple field datasets, assess predictive and prognostic performance metrics, and iteratively refine the system to support adaptive maintenance scheduling informed by probabilistic health forecasts.

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BIOGRAPHIES

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Jose I. Aizpurua received the Eng., M.Sc., and Ph.D. degrees from Mondragon University (MU), Arrasate, Spain, in 2010, 2012, and 2015, respectively. He was a Visiting Researcher with the Dependable Intelligent Systems Group, University of Hull, Hull, U.K., in 2014; a Research Associate with the Institute for Energy and Environment, University of Strathclyde, Glasgow, U.K., from February 2015 to December 2018; and a Lecturer and a Researcher with the Department of Electronics and Computer Science, MU, from February 2019 to September 2024. He is currently a Ramon y Cajal Research Fellow with the Faculty of Computer Science, Department of Computer Science and Artificial Intelligence, University of the Basque Country (UPV/EHU), Donostia-San Sebastián, Spain, and an Ikerbasque Research Fellow. His research interests include the development of intelligent solutions for the power and energy sector.